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Regional Income Distribution in the European Union: A Parametric Approach *

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Abstract

This work studies trends in income distributions and inequality in the European Union using data from the European Union Statistics on Income and Living Conditions. We model the income distribution for each country under a Dagum distribution assumption and using maximum likelihood techniques. We use parameter estimates to form distributions for regions defined as finite mixtures of the country distributions. Specifically, we study the groups of "new" and "old" countries depending on the year they joined the European Union. We provide formulae and estimates for the regional Gini coefficients and Lorenz curves and their decomposition for all the survey years from 2007 through 2011. Our estimates show that the "new" European Union countries have become richer and less unequal over the observed years, while the "old" ones have undergone a slight increase in inequality which is however not significant at conventional levels.

JEL Codes: D31, D63, C13

Keywords: income distribution, finite mixtures, inequality, Gini decomposition, European Union

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1 Introduction

The European Union experienced several enlargements since the establishment of its predecessor, the European Economic Community, in 1957, from only six founding states - Belgium, France, Italy, Luxembourg, the Netherlands, and (West) Germany - to 28 Member States today. One of the major enlargements happened in 2004 when countries from Central and Eastern Europe joined the European Union. The change in composition modified the income distribution and inequalities within the European Union. Even though it is currently the world's largest economy, generating a nominal gross domestic product of approximately 14.303 trillion Euros according to International Monetary Fund (2014), if we look into its Member States individually, we see large differences in the income distribution between and within them.

This work adds to the literature on the distribution of income and inequality in the European Union, both for individual countries and regionally. The income distribution in European Union countries has been much researched either as part of the world distribution of income with inequality analyses based on grouped income data (for instance, Chotikapanich et al. (2007, 2012); Milanović (2002, 2005, 2012); Sala-i-Martín (2006)), or separately in inequality analyses at the country level (e.g. Filauro (2017); Tóth and Medgyesi (2011)). Jenkins et al. (2013) have studied the evolution of income distribution during the Great Recession in 21 rich OECD countries, Brzeziński (2018) has analyzed the income inequality in Central and Eastern Europe, while Anderson et al. (2018) have focused on income classification in the Euro zone as an entity.

Like many recent studies, we use representative microdata from the European Union Statistics on Income and Living Conditions (EU-SILC) cross-sectional survey to study both inequality in individual countries, and in broader country groupings as "new" and "old" Member States. The "new" countries are those which entered the European Union after 2004 and the "old" are those which entered before 2004. We selected 2004 as the splitting year since this marked the largest expansion of the European Union.

This work makes three contributions to the literature. First, we provide new parametric model estimates for the income distribution of the European Union as a whole, for multi-country regional groupings, and for individual countries for each year from 2007 to 2011. We obtain the regional models as finite mixtures of the individual countries distributions. To derive the models, we fit the Dagum distribution via maximum likelihood techniques to the income data available for each of the European Union countries. Second, we provide formulae for the Gini coefficient and the Lorenz curve implied by Dagum distribution mixture models. We introduce an efficient way for computing the total Gini coefficient numerically and decompose the regional Gini coefficients into within- and between-country contributions. Third, our results show that the region formed by the "new" Member States is more unequal and less wealthy than the region formed by the "old" ones and we observe that inequality in the "new" countries contributes substantially to overall inequality for the European Union as a whole. However, looking at the evolution of income distribution over time, we find that the "new" Member States have become, on average, wealthier and more equal over time, while the "old" Member States have undergone a slight increase in inequality. We provide `R` code for replicating estimations in Appendix A (R Core Team (2014)).

Using parametric models for studying income distributions has several advantages. We can represent the income distribution of a country with a small number of estimated parameters (Chotikapanich et al. (2007, 2012); Hajargasht et al. (2012)), from which the distribution in larger entities, in our case regions, can be obtained in a straightforward way. We exploit this in Section 4 below. The model parameters often also possess an economic interpretation, which allows to gain insights about the causes of the evolution of income distribution over time or interpret the differences between income distributions across countries (Brzeziński (2013)). Explicit formulae are available for many poverty and inequality measures as functions of the parameters of the theoretical income distribution. Benefits of parametric models in terms of estimation stability are also put forward in Graf and Nedyalkova (2014).

Specifically, the Dagum distribution has been used successfully for fitting data from various sources (Dagum (1977); García Pérez and Prieto Alaiz (2011); Kleiber and Kotz (2003)). Dagum (1977) aimed to find a distribution that would capture the heavy tails present in wealth distributions as well as permitting interior modes, thereby outperforming the more classical Pareto and lognormal distributions. In a comprehensive empirical study involving 11 parametric models and 23 countries, Bandourian et al. (2003) observed that the Dagum distribution was the best-fitting three-parameter distribution in more than 80% of the cases. Kleiber (2008) provides further references on the empirical performance of the Dagum distribution. The distribution may sometimes be outperformed by a distribution with additional parameters such as the generalized beta distribution of the second kind (GB2), but the effect is often marginal (Bandourian et al. (2003)) at the cost of introducing significant empirical and analytical complexity. Our analysis confirms the good performance and the tractability of the Dagum distribution for modeling income distributions.

The work is structured as follows. The EU-SILC data are described in Section 2. Section 3 collects some basic properties of the Dagum distribution, describes model fitting via maximum likelihood and bootstrap inference, and provides an assessment of goodness-of-fit. Also, in Section 3.3, we give analytical expressions for the regional Lorenz curves and Gini coefficients. Country-specific and regional results appear in Section 4. Finally, Section 5 provides concluding remarks.

2 Data

The EU-SILC provides nationally representative data on income, poverty, social exclusion and living conditions for all of the European countries. The EU-SILC survey for each country is provided to the statistical office of the European Union (Eurostat) by the relevant national statistical institutes which collect the data according to a common overarching methodology suggested by Eurostat. EU-SILC is the basis for calculation of commonly-agreed indicators on poverty and social inclusion in EU countries (Atkinson et al. (2017)). EU-SILC data have also been used by academics for income modeling and inequality analysis across Europe (see e.g. Anderson et al. (2018); Aristei and Perugini (2010); Filauro (2017); Graf and Nedyalkova (2014); Longford et al. (2012); Tóth and Medgyesi (2011)) and for examining poverty measures (e.g. Fabrizi et al. (2011); Jenkins and Van Kerm (2011)).

We use EU-SILC cross-sectional survey data for the years 2007-2011. The income reference period is one year earlier than the year of the survey, since the total income collected in EU-SILC is the income for the calendar year previous to the interview (except for the UK and Ireland; see Appendix B). We model and compare the distributions of personal income for each of the European Union countries except Ireland (as it is not included in the EU-SILC 2011 survey), Malta (since it is not included in the EU-SILC

2007 and 2008 surveys) and Croatia (since it entered the European Union in 2013). Table 5, in Appendix B, presents descriptive statistics for the 2011 data.

We focus on the equivalised disposable income computed in purchasing power parities and apply cross-sectional weights to account for population size. For more details on the variables used, see again Appendix B.

Section 4 below presents an analysis of European Union regions composed of "new" and "old" countries depending on the year they joined the European Union (after or before 2004). In Table 1, we provide the so-defined "old" and "new" European Union countries along with country codes in brackets as given by Eurostat (2011). Table 1 can be used as a reference for the "old" and "new" regions and their respective graphs and explanations provided later in this work. From now on, whenever we refer to the (whole) European Union in this work, we mean the countries listed in Table 1 under Old EU Member States plus the New EU Member States, excluding Croatia, Malta and Ireland.

Table 1: European Union regional classification

Old EU	New EU	EU
Austria (AT)	Bulgaria (BG)	All without:
Belgium (BE)	Cyprus (CY)	Croatia (HR)
Denmark (DK)	Czech Republic (CZ)	Ireland (IE)
Finland (FI)	Estonia (EE)	Malta (MT)
France (FR)	Hungary (HU)	
Germany (DE)	Latvia (LV)	
Greece (EL)	Lithuania (LT)	
Italy (IT)	Poland (PL)	
Luxembourg (LU)	Romania(RO)	
Netherlands (NL)	Slovakia (SK)	
Portugal (PT)	Slovenia (SI)	
Spain (ES)		
Sweden (SE)		
United Kingdom (UK)		

3 Methodology

This section describes the methodology which we applied for fitting the income data from EU-SILC using Dagum distributions. In Section 3.1, we provide some basic characteristics of the distribution. In Section 3.2, we explain how we employ the maximum likelihood approach for model fitting. Section 3.3 provides all the necessary components for regional analysis of income distribution and inequality with the Dagum distribution. It gives closed-form expressions for the regional densities, the regional Lorenz curves, the between-country and within-country Gini coefficients and explains how regional Gini coefficients were estimated. Finally, Section 3.4 describes a parametric bootstrap method that was used to obtain standard errors.

3.1 The Dagum distribution

The Dagum distribution is a three-parameter distribution, $D(\eta)$, where η is the triple (a, b, p). We use a parametrization of the Dagum distribution given in Kleiber and Kotz (2003) that slightly differs from the parameterization originally used in Dagum (1977). Its density is

$$f(x;\eta) = \frac{apx^{ap-1}}{b^{ap}[1+(x/b)^a]^{1+p}}, \quad x > 0, \tag{1}$$

where a, b, and p are positive real numbers. When η is obvious from the context, we write only $f(x)$.

The cumulative distribution function can be written in closed form as

$$F(x;\eta) = \left[1 + \left(\frac{x}{b}\right)^{-a}\right]^{-p}, \quad x > 0. \tag{2}$$

The quantile function can also be written in closed form as

$$Q(u;\eta) = b\left[u^{-1/p} - 1\right]^{-1/a}, \quad 0 < u < 1. \tag{3}$$

The mean of the Dagum distribution equals

$$\mu = \frac{b\Gamma(p+1/a)\Gamma(1-1/a)}{\Gamma(p)}, \tag{4}$$

where $\Gamma(p)$ is the gamma function.

The Lorenz curve of the Dagum distribution is

$$L(u) = I_z\left(p + \frac{1}{a}, 1 - \frac{1}{a}\right), \quad 0 \leq u \leq 1, \tag{5}$$

where $z = u^{1/p}$ and $I_z(p,q)$ is the incomplete beta function ratio defined as $I_z(p,q) = \frac{1}{B(p,q)} \int_0^z u^{p-1}(1-u)^{q-1}du$, $0 \leq z \leq 1$, with $B(p,q)$ the beta function (Kleiber and Kotz (2003)).

The Gini coefficient is

$$G = \frac{\Gamma(p)\Gamma(2p+1/a)}{\Gamma(2p)\Gamma(p+1/a)} - 1. \tag{6}$$

3.2 Estimation

We employ maximum likelihood to estimate the parameters of the distribution. To account for unequal sampling probabilities, we weight the likelihood by the cross-sectional weights provided with the data. Let N be the number of people in the given sample, x_i the equivalised income of person i and w_i the cross-sectional weight of person i. The weighted log-likelihood $l(\eta)$, with $\eta = (a, b, p)$, is

$$l(\eta) = \sum_{i=1}^{N} w_i \log(f(x_i;\eta)), \tag{7}$$

where $f(x;\eta)$ is the Dagum density given in formula (1).

We maximize the log-likelihood function $l(\eta)$ with respect to the Dagum distribution parameters a, b, and p using the `R` programming language (R Core Team (2014)). For optimization, we use the `nlminb` function. The initial values a_0, b_0 and p_0 for the parameters a, b, and p are $a_0 = 2$ and $p_0 = 0.4$ for all countries, whereas for each country b_0 is set to the mean income of the respective country.

3.3 Regional income distribution and inequality

Once we have estimated the three parameters of the Dagum distribution for each country, we form groups of countries and compute the regional income distribution and inequality for each region. This can be achieved by computing regional densities and distribution functions which are sums of the densities, or respectively distribution functions, of all countries in a given region weighted by their population sizes. Formally, given K countries each with parameter vector η_k, $k = 1, \cdots, K$, density functions $f_k(x) = f(x; \eta_k)$, and population shares $\pi_1, \pi_2, \cdots, \pi_K$, the regional density is given by (Chotikapanich et al. (2012))

$$f(x) = \sum_{k=1}^{K} \pi_k f_k(x), \tag{8}$$

with $f_k(x)$ as in equation (1). The regional cumulative distribution function is

$$F(x) = \sum_{k=1}^{K} \pi_k F_k(x), \tag{9}$$

with $F_k(x) = F(x; \eta_k)$ given in equation (2). The population shares $\pi_1, \pi_2, \cdots, \pi_K$ are computed using the total population size (see Appendix B).

The regional mean income is

$$\mu = \sum_{k=1}^{K} \pi_k \mu_k, \tag{10}$$

with μ_k as given in equation (4).

The regional cumulative income shares $\psi(x)$ are analogous to the ones given by Chotikapanich et al. (2012) for the beta-2 distribution. Here, for the Dagum distribution the cumulative income shares, $\psi(x)$, are computed as

$$\begin{aligned}\psi(x) &= \frac{1}{\mu}\int_0^x z f(z) dz = \frac{1}{\mu}\sum_{k=1}^{K} \pi_k \int_0^x z f_k(z) dz \\ &= \frac{1}{\mu}\sum_{k=1}^{K} \frac{\pi_k b_k I_y\left(p_k + \frac{1}{a_k}, 1 - \frac{1}{a_k}\right)\Gamma\left(p_k + \frac{1}{a_k}\right)\Gamma\left(1 - \frac{1}{a_k}\right)}{\Gamma(p_k)},\end{aligned} \tag{11}$$

where $I_y(p, q)$ is the incomplete beta function ratio defined as above, now with $y = \frac{(x/b)^a}{1+(x/b)^a}$ and μ as given in equation (10). To graphically represent inequality, we obtain Lorenz curves by plotting the regional cumulative income shares $\psi(x)$ (given in equation (11)) against the regional cumulative shares of population $F(x)$ (given in equation (9)).

Finally, the regional Gini coefficient can be written as (Chotikapanich et al. (2012))

$$G = -1 + \frac{2}{\mu}\sum_{j=1}^{K}\sum_{i=1}^{K} \pi_j \pi_i \int_0^\infty y F_j(y) f_i(y) dy, \tag{12}$$

where μ is the regional mean income given in equation (10), $F_j(y)$ is the distribution function for country j given in equation (2), and $f_i(y)$ is the income density for country

i given in equation (1). The integral appearing in equation (12) can be estimated numerically. We have split the integration into ranges and summed the results up, using the function `integrate` in `R`, which performs adaptive quadrature.

The regional Gini coefficient can be decomposed into a within-country and a between-country component (along with an interaction term) to capture how much aggregate inequality is driven by income differences across countries and how much is driven by income differences within countries: $G = G_B + G_W + I$ (see Lambert and Aronson (1993)).

The first term G_B captures how much differences in income between countries accounts for the aggregate inequality and is obtained if every income in every country is replaced with the mean income of the relevant country. We compute the between-country Gini coefficient G_B as (Lambert and Aronson (1993); Chotikapanich et al. (2012))

$$G_B = \frac{1}{2\mu} \sum_{j=1}^{K} \sum_{i=1}^{K} \pi_j \pi_i |\mu_j - \mu_i|, \tag{13}$$

where μ_i is the mean income for country i given in equation (4), and μ is the regional mean income given in equation (10).

G_W measures the contribution of within-country inequality and is obtained as a weighted sum of the Gini coefficients for all countries (see Chotikapanich et al. (2012); Lambert and Aronson (1993))

$$G_W = \sum_{j=1}^{K} \pi_j s_j G_j, \tag{14}$$

the weights are the products of the population shares π_j and income shares $s_j = \pi_j \mu_j / \mu$, and G_j is the Gini coefficient for country j given in equation (6).

The interaction term I is the difference between the regional Gini coefficient and the between-country and the within-country Gini coefficients, namely $I = G - G_B - G_W$. I is zero if the income ranges for each country do not overlap. Recently, Anderson et al. (2018) used the interaction term to define a "non-segmentation factor".

Figure 1 provides a graphical representation of the Gini decomposition for two imag-

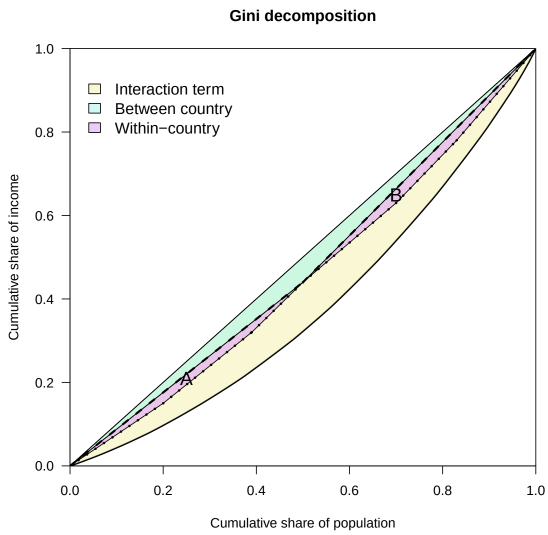


Figure 1: Gini decomposition

inary countries A and B. The total Gini coefficient, G, for countries A and B is twice the area between the diagonal line of perfect equality and the Lorenz curve which is the solid black curve on the plot. The between-country Gini coefficient is twice the area between the diagonal line of perfect equality and the perfect equality lines for countries A and B when all their citizens receive incomes equal to the mean income of the respective country. The within-country Gini components are twice the area between the between-country Gini components perfect equality lines and the Lorenz curves corresponding to the weighted Gini coefficients for each respective country. The interaction term is the residual to the total Gini coefficient, G; that is, it is twice the area between the Lorenz curves corresponding to the within-country Gini coefficients and the Lorenz curve corresponding to the total Gini coefficient (the yellow area on the plot).

3.4 Inference and goodness-of-fit

To obtain the standard errors of the distribution parameters, the Gini coefficients, the means and the medians as estimated with our model, we employ a parametric bootstrap. Following Efron and Tibshirani (1993), we proceed as follows::

1. We draw $1,000$ samples of the same size as the original data from the parametric estimate of the population $D(\hat{\eta})$.

2. We apply the maximum likelihood approach (see section 3.2) to each bootstrap sample and obtain the corresponding parametric estimates $\hat{\eta}^*(s), s = 1, \cdots, 1,000$. With these estimates, we compute the distribution parameters, the Gini coefficient, the mean and the median of each bootstrap sample.

3. We estimate the standard errors of the distribution parameters, the Gini coefficient, the mean and the median by the corresponding sample standard deviations of all the replications.

An increase of the number of bootstrap replications did not change the results appreciably. We compute the standard errors of the regional Gini coefficients analogously.

To investigate to what extent the observed microdata are consistent with a Dagum distribution, we assess goodness-of-fit in various ways. First, we employ the Kolmogorov-Smirnov test, which utilizes the discrepancy between the estimated theoretical distribution function and the empirical one (e.g., Stephens (1986)). Employing a parametric bootstrap, we perform the test as given in Cowell et al. (2015). At the 1% significance level the null hypothesis that the sample comes from a Dagum distribution is not rejected for roughly a dozen countries per year.

Significance testing at conventional levels is perhaps not fully satisfactory for the sample sizes at hand. As a further check of goodness-of-fit, we look at the kernel density and the quantile-quantile plots of our estimates versus the empirical ones. First, the estimated Dagum density and a kernel density estimate are plotted. The kernel density is computed with the function `locfit` from the `R` package of the same name (Loader (2013)) using the default settings, that is, a tricube kernel function and a nearest neighbour bandwidth covering 70% of the data (`alpha = 0.7`) as well as appropriate weights.

For each country, the density curves drawn using the estimated distribution parameters and the kernel density curves are very close to each other, which indicates a good model fit. Figure 2 shows the density plots for some of the observed countries (the choice of countries is detailed in Section 4 below, the parameter estimates for these countries are given in Table 2).

Quantile-quantile plots are shown for the same countries in Figure 3. The empirical

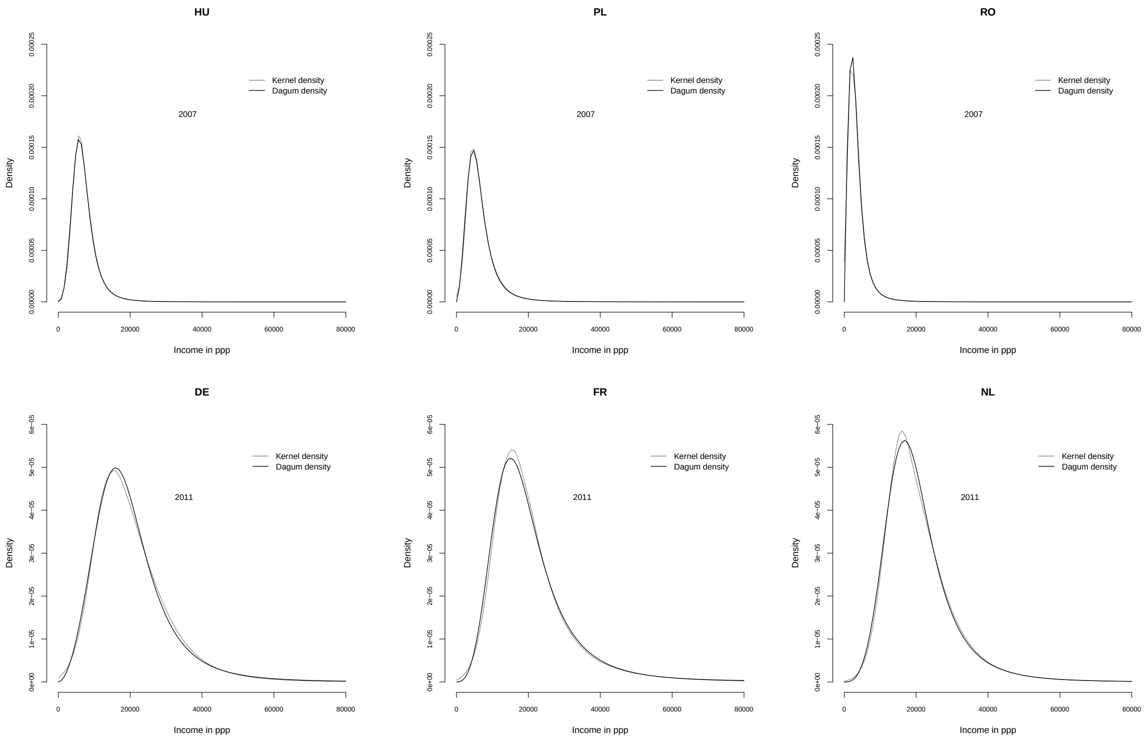


Figure 2: Kernel density versus estimated Dagum density

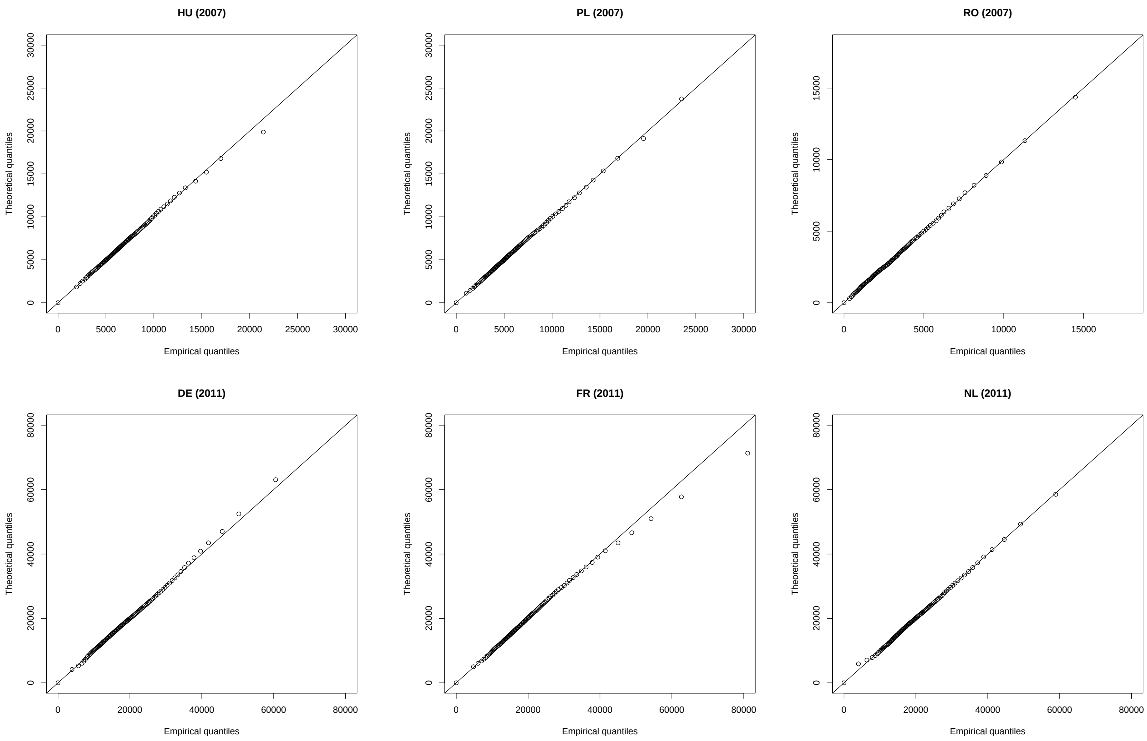


Figure 3: Q-Q plots (empirical versus theoretical quantiles)

versus the theoretical quantiles are plotted using only the percentiles of the microdata in order to avoid overplotting. There are moderate discrepancies only in the right tail of the distribution. For reasons of space not all combinations of years and countries are provided here.

4 Results

4.1 Country-specific results

Table 2 provides the Dagum parameters for selected countries for the years 2007 and 2011, namely three "old" and three "new" European Union countries. (A complete list with all parameters for all observed years and countries can be found in Table 6 in Appendix C.) Here, the "old" EU is represented by Germany, France and the Netherlands. The "new" EU is represented by Hungary, Poland and Romania. Table 2 shows that the estimates of the national shape parameters a and p are fairly similar for both regions, whereas the estimates of the scale parameter b differ between the regions. From formula (4), the mean of the Dagum distribution, this reflects that "old" EU countries are typically much richer than "new" EU countries.

Table 2: Estimated parameters for Dagum distribution for selected countries and years

	2007			2011		
Country	$\hat{a}$	$\hat{b}$	$\hat{p}$	$\hat{a}$	$\hat{b}$	$\hat{p}$
Hungary	4.1839	6937.75	0.8263	3.6470	6934.27	1.0294
Poland	3.2601	6152.88	0.8241	3.4433	9073.83	0.7843
Romania	2.9747	3615.72	0.6131	3.7352	4903.64	0.4816
Germany	3.7768	19570.74	0.7432	3.8206	20394.01	0.7560
France	3.8277	15317.79	0.9647	3.3272	17390.27	1.1053
Netherlands	3.8529	17307.33	1.0571	4.0893	19274.93	0.9489

With the estimated parameters for a, b and p, we can estimate the Gini coefficient, the mean, the median and the Lorenz curves according to the analytical expressions given in Section 3.1. Table 3 provides the parametric estimates next to the empirical estimates for all the considered countries for 2007 and 2011 along with standard errors (in brackets) estimated using a parametric bootstrap. The empirical estimates are directly computed with the unit record income data. The parametric estimates are generally very close to the estimates computed directly from the sample data.

Table 3: Gini coefficients and medians for all countries and selected years

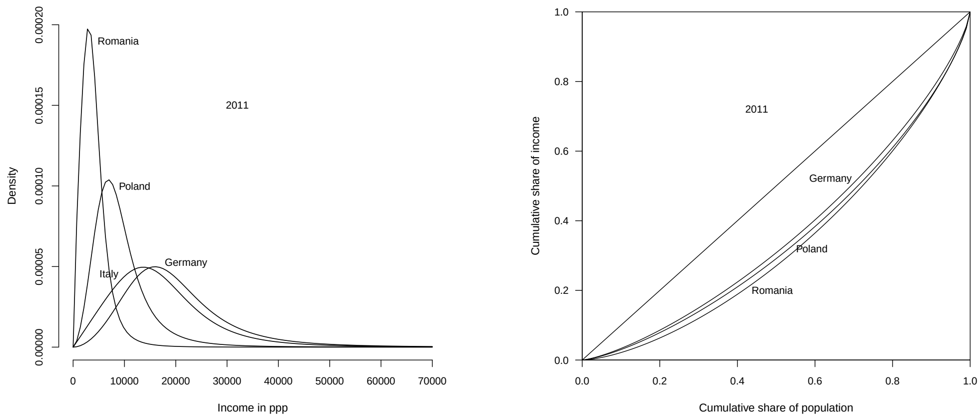
	Gini coefficient		SE(Gini	Median		SE(Median
	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)
2007						
AT	0.2619	0.2579	(0.003)	17808.03	17920.23	(101.92)
BE	0.2623	0.2603	(0.003)	16311.07	16252.42	(97.66)
BG	0.3529	0.3488	(0.004)	3298.93	3288.03	(33.35)
CY	0.2978	0.2886	(0.005)	18244.05	18033.35	(153.31)

CZ	0.2527	0.2477	(0.002)	8840.71	8934.98	(40.25)
DE	0.2989	0.2871	(0.002)	17324.67	17452.31	(82.75)
DK	0.2451	0.2277	(0.002)	16865.51	16901.41	(87.78)
EE	0.3341	0.3280	(0.004)	6490.87	6519.01	(55.99)
EL	0.3427	0.3406	(0.004)	11436.55	11456.10	(91.48)
ES	0.3126	0.3140	(0.003)	13117.82	13234.11	(71.27)
FI	0.2616	0.2543	(0.002)	15240.21	15097.27	(68.31)
FR	0.2656	0.2636	(0.002)	15148.29	15118.76	(68.56)
HU	0.2555	0.2518	(0.002)	6490.14	6499.80	(32.64)
IT	0.3222	0.3178	(0.002)	14404.92	14459.45	(61.23)
LT	0.3382	0.3414	(0.005)	5713.35	5805.62	(50.84)
LU	0.2736	0.2768	(0.004)	26839.20	27010.84	(216.14)
LV	0.3536	0.3629	(0.005)	5515.25	5585.13	(55.73)
NL	0.2725	0.2561	(0.002)	17537.36	17653.52	(79.61)
PL	0.3218	0.3216	(0.002)	5608.55	5651.94	(26.93)
PT	0.3691	0.3814	(0.006)	8950.76	9136.22	(88.12)
RO	0.3783	0.3808	(0.004)	2876.40	2818.82	(23.36)
SE	0.2339	0.2306	(0.002)	15907.47	15990.61	(79.35)
SI	0.2330	0.2341	(0.002)	12917.11	13022.78	(58.92)
SK	0.2447	0.2397	(0.003)	5607.93	5647.24	(33.27)
UK	0.3276	0.3228	(0.003)	18662.18	18637.11	(113.02)
2011						
AT	0.2631	0.2608	(0.003)	20249.83	20277.48	(124.67)
BE	0.2620	0.2593	(0.003)	17992.35	17809.84	(110.18)
BG	0.3509	0.3495	(0.004)	5699.85	5668.53	(46.35)
CY	0.2914	0.2902	(0.004)	19238.34	19250.17	(160.83)
CZ	0.2524	0.2471	(0.002)	9858.34	9991.60	(47.82)
DE	0.2877	0.2824	(0.002)	18240.69	18335.67	(82.29)
DK	0.2666	0.2542	(0.003)	18680.15	18769.92	(121.48)
EE	0.3189	0.3252	(0.004)	7333.56	7497.71	(66.16)
EL	0.3348	0.3285	(0.004)	11479.69	11461.45	(94.19)
ES	0.3365	0.3342	(0.002)	12905.98	13245.41	(73.61)
FI	0.2581	0.2550	(0.002)	17742.45	17651.26	(83.69)
FR	0.3082	0.2939	(0.003)	18053.47	18120.09	(86.51)
HU	0.2681	0.2723	(0.002)	7016.77	7010.78	(31.07)
IT	0.3189	0.3120	(0.002)	15513.43	15585.70	(66.97)
LT	0.3284	0.3314	(0.004)	6164.57	6221.04	(55.27)
LU	0.2707	0.2747	(0.003)	26666.64	26783.74	(178.39)
LV	0.3534	0.3582	(0.004)	5665.68	5845.11	(50.30)
NL	0.2526	0.2479	(0.002)	18748.29	18932.11	(81.74)
PL	0.3105	0.3091	(0.002)	8206.76	8195.16	(43.37)
PT	0.3424	0.3462	(0.005)	9583.17	9649.25	(76.63)
RO	0.3328	0.3354	(0.003)	3553.66	3586.19	(27.66)
SE	0.2430	0.2398	(0.002)	18473.53	18452.82	(100.75)
SI	0.2383	0.2379	(0.002)	13796.71	13817.96	(61.81)
SK	0.2567	0.2536	(0.003)	8855.06	9007.66	(59.18)
UK	0.3297	0.3217	(0.003)	17190.29	17508.41	(113.50)

A complete list with the Gini coefficients, mean and median estimates for all the observed years and countries is available in Table 7 in Appendix C.

It is interesting to note that the "new" countries experienced a decrease in inequality from 2007 to 2010 (according to the estimated Gini coefficients), which was followed in 2011 by a slight increase in the inequality. Romania, for example, which is one of the newest European Union countries (Member State since 2007) had a Gini coefficient of 0.380 in 2007 which was continuously decreasing and reached the value 0.335 in 2011. On the other hand, the "old" European countries did not experience a significant change in their Gini coefficients or the respective inequality.

To enable comparison of the "new" and "old" Member States, in Figure 4 we have plotted the densities and the Lorenz curves for selected countries for the year 2011. It is obvious that the "old" countries have higher incomes than the "new" ones, but also more equal than the "new" ones. This can be seen in the Lorenz curve plots (see Figure 4b) and is also shown by the estimated Gini coefficients and medians.



(a) Density functions (b) Lorenz curves

Figure 4: Densities and Lorenz curves for selected countries

4.2 Regional results

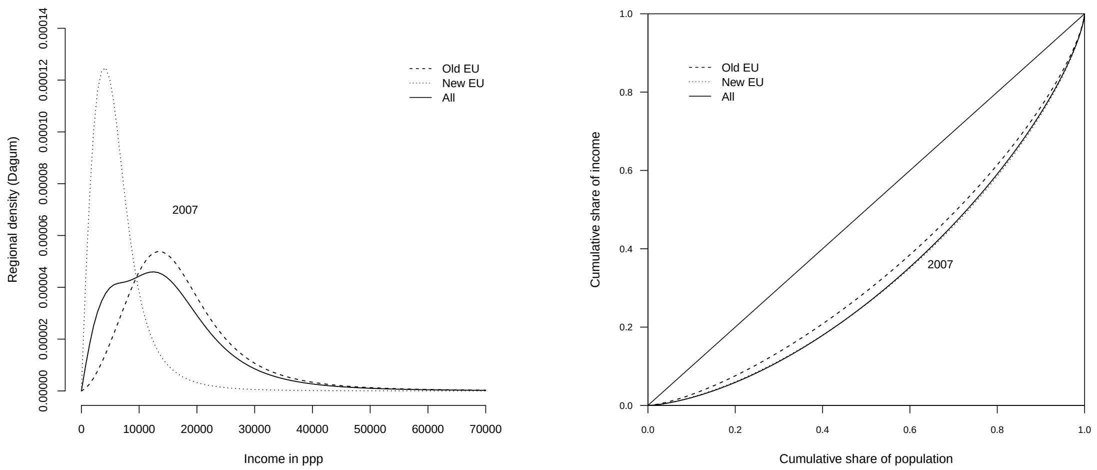
For the regional analysis, we compute the regional Gini coefficients and their within-country and between-country components for each region and year as described in Section 3.3.

Table 4 provides the estimates for the predefined regions along with standard errors (in brackets) estimated using the parametric bootstrap as explained in Section 3.4 but with 100 bootstrap replications due to time constraints. Note that the between-country, the within-country Gini coefficients and the interaction terms given in Table 4 sum up to the total regional Gini coefficients. The within-country component of the Gini coefficient is very small for all of the regions and the between-country Gini component is much larger for the "new" countries and the whole European Union than for the "old" ones, which can be also seen in the plots of the regional Lorenz curves. The inequality in the "old" European Union regions comes mainly from the interaction term which means that there is a large overlap in incomes. On the other hand, the interaction term is much smaller in the "new" European Union region, meaning that there is less of an overlap in incomes and higher between-country inequality. We can observe a decrease in the Gini coefficient from 2007 to 2011 in the "new" Member States, while for the "old" Member States, a slight increase is observed.

Table 4: Regional Gini coefficients

	Old EU	SE(Gini)	New EU	SE(Gini)	EU	SE(Gini)
Gini (2007)	0.306	(0.00029)	0.370	(0.00046)	0.363	(0.00021)
Between	0.078	(0.00036)	0.191	(0.00037)	0.185	(0.00025)
Within	0.042	(0.00005)	0.064	(0.00020)	0.032	(0.00003)
Interaction	0.186		0.115		0.146	
Gini (2009)	0.303	(0.00028)	0.351	(0.00041)	0.349	(0.00019)
Between	0.059	(0.00035)	0.165	(0.00032)	0.156	(0.00019)
Within	0.042	(0.00005)	0.063	(0.00017)	0.031	(0.00003)
Interaction	0.202		0.123		0.162	
Gini (2011)	0.308	(0.00029)	0.354	(0.00042)	0.350	(0.00020)
Between	0.069	(0.00033)	0.176	(0.00032)	0.159	(0.00022)
Within	0.042	(0.00005)	0.064	(0.00016)	0.031	(0.00003)
Interaction	0.197		0.114		0.160	

Figure 5a shows the regional mixture density functions of the “new” European Union countries versus the “old” ones together with the mixture distribution for the whole European Union for the year 2007. Figure 5b shows the respective regional Lorenz curves. The “new” countries are more unequal than the “old” ones. The regional Lorenz curve for the whole European Union is almost identical with the regional Lorenz curve for the “new” countries, implying that the inequality in the European Union as a whole is almost the same as in the “new” countries, which is also confirmed by the regional Gini coefficients.



(a) Regional density function

(b) Regional Lorenz curves

Figure 5: Regional densities and Lorenz curves (2007)

Figure 6 shows the temporal changes in the regional densities and Lorenz curves for the whole European Union, the “old” region and the “new” region from 2007 to 2011. Additionally, in the Lorenz curves plots we have plotted the regional between-country Lorenz curves which reflect the inequality between countries for the given years.

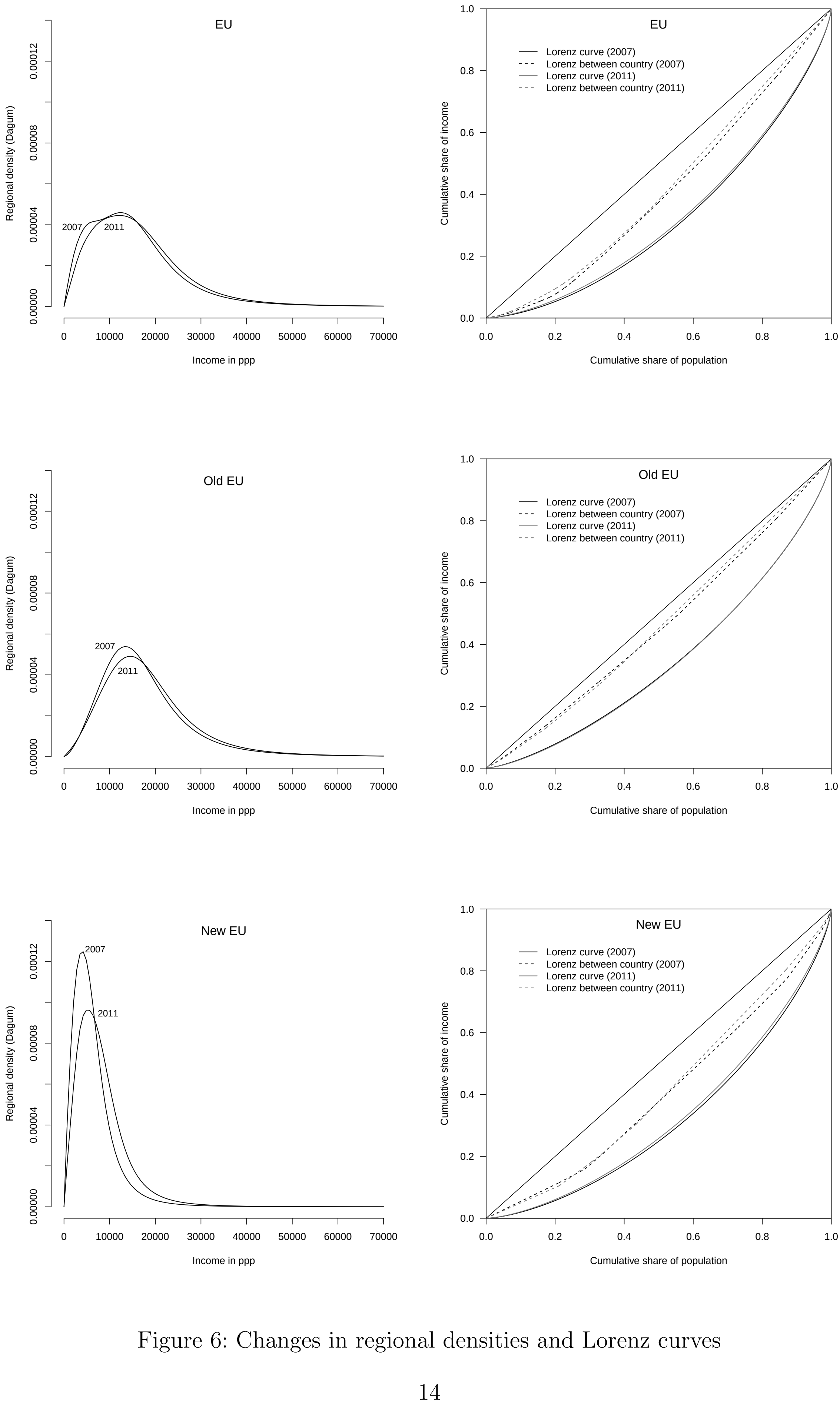


Figure 6: Changes in regional densities and Lorenz curves

The between-country inequality is much higher in the "new" region than in the "old" region. But we can observe a decrease in the between-country inequality in the "new" region and a decrease in the overall inequality from 2007 to 2011. On the other hand, for the "old" region there is a minor increase in the overall inequality, while the between-country inequality slightly decreased from 2007 to 2011.

5 Concluding remarks

We investigated the income distribution in the European Union as a whole and divided into a "new" and an "old" region for all the years from 2007 through 2011. We modeled the distribution parametrically as a finite mixture of country-specific distributions. The country-specific distributions were estimated using maximum likelihood techniques employing the Dagum distribution to EU-SILC microdata. Our estimates summarize the structure of the whole income distribution and inequality in just three parameters per country. The method performed well and led to results which agree well with the descriptive statistics of the microdata. Further, we estimated the regional Gini coefficients, the regional Lorenz curves and their decomposed counterparts.

Employing the above-mentioned technique to analyze EU-SILC income data, we found that there are still large differences in income distribution among the different European Union countries. The countries that joined more recently still have to catch up with the older Member States which have become fairly homogeneous over the years. Our results show that the "new" Member States are more unequal and less wealthy than the "old" ones. Moreover, we show that the inequality in the "new" countries contributes a lot to the inequality in the whole European Union. It is interesting to note that the years of the Great Recession impacted the "new" and the "old" Member States in a different way: The "new" Member States have become on average richer and more equal over recent years, while the "old" Member States have undergone a slight increase in inequality which however is not significant at conventional levels.

On the methodological side, our results confirm that the Dagum distribution provides an appropriate fit to the income distribution in the observed countries. Furthermore, we show how to model the regional distribution of income and inequality from country fits of the Dagum distribution parameters and provide the required formulae.

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Appendices

A. Code

This appendix provides the R code used in this paper for estimating the Dagum distribution parameters a, b and p.

```
########################################################################
## 1. Common functions.

## Dagum density function as in formula (I.1)
ddagum <- function(x, a, b, p, log = FALSE)
{
  lddagum <- log(a) + log(p) + (a*p - 1)*log(x)
             - a*p*log(b) - (1+p)*log(1 + (x/b)^a)
  if (log == FALSE)
    ft <- exp(lddagum)
  else ft <- lddagum
  ft
}

## Weighted log-likelihood as in formula (I.7)
wll <- function(a, b, p, x, distr, weights)
{
  ddistname <- get(paste("d", distr, sep=""))
  nweights <- weights[which((x > 0))]
  ncens <- x[which((x > 0))]
  wll <-  - sum(nweights*ddistname(ncens, a, b, p,
             log=TRUE))
  return(wll)
}

########################################################################
# 2. Country processing code

## For each country read input data.
eqincome <- c(......) # from microdata set
hweight <- c(......) # from microdata set
curr_mean <- weighted.mean(eqincome, hweight)

## Give initial values for a, b and p.
initial_values <- c(2, curr_mean, 0.4)

## Optimize the a, b and p distribution parameter values
nlminb(initial_values, function(theta) {
      wll(theta[1], theta[2], theta[3], eqincome,
               distr= "dagum", weights = hweight)},
      lower = c(0.01, 0.01, 0.01), upper = c(Inf, Inf, Inf))
```

B. Data definitions and preprocessing

In this appendix the survey data variables used in this work are explained and defined. In terms of variables, first we use the equivalised disposable household income (`edhi`) which is given in Euro for all countries. This is the variable `HX090` in EU-SILC. The variable `HX090` is defined as

$$\mathtt{HX090} = \frac{\mathtt{HY020} * \mathtt{HX025}}{\mathtt{HX050}},$$

where `HY020` is the total disposable household income (defined below), `HX050` is the equivalised household size (defined later), and `HY025` is a within-household non-response inflation factor (explained below).

To make the income comparable across countries, we compute it in purchasing power parities (`ppp`) which together with the exchange rates (`xrate`) are provided by Eurostat. We take the ppps and the exchange rates from the file "PPP rates X-sectional from 06-01-2015" available in the UDB documentation on CIRCABC. For countries which are members of the Euro Area, we compute the income in ppps as

$$\mathtt{edhi\_ppp} = \mathtt{edhi/ppp},$$

and for countries which are not members of the Euro Area as

$$\mathtt{edhi\_ppp} = \mathtt{(edhi*xrate)/ppp},$$

defined as in Eurostat (2011a). To account for population size, we use the household cross-sectional weight (`DB090` in EU-SILC).

The EU-SILC cross-sectional surveys, except for the United Kingdom and Ireland, usually have the income reference period as the previous calendar year (Atkinson and Marlier (2010)). For the United Kingdom the income reference period is the current year and for Ireland it is the previous twelve months.

Next, we provide the definitions of the total disposable household income (`HY020`) and the equivalised household size (`HX050`) as given by Eurostat.

The **total disposable household income (`HY020`)** can be computed as (see Eurostat, 2011b):

- the sum for all household members of gross personal income components, namely
  - gross employee cash or near cash income (`PY010G`),
  - company car (`PY021G`),
  - gross cash benefits or losses from self-employment (including royalties) (`PY050G`),
  - pensions received from individual private plans (other than those covered under ESSPROS) (`PY080G`),
  - unemployment benefits (`PY090G`),
  - old-age benefits (`PY100G`),
  - survivor' benefits (`PY110G`),
  - sickness benefits (`PY120G`),

  - disability benefits (PY130G),
  - education-related allowances (PY140G);
- plus gross income components at household level, namely
  - income from rental of a property or land (HY040G),
  - family/-children-related allowances (HY050G),
  - social exclusion not elsewhere classified (HY060G), housing allowances (HY070G),
  - regular inter-household cash transfers received (HY080G),
  - interests, dividends, profit from capital investments in unincorporated business (HY090G),
  - income received by people aged under 16 (HY110G);
- minus
  - regular taxes on wealth (HY120G),
  - regular inter-household cash transfer paid (HY130G),
  - tax on income and social insurance contributions (HY140G).

The **equivalised household size (**HX050**)** is defined as (see Eurostat (2011a)):

$$\texttt{HX050} = 1 + 0.5 * (\texttt{HM}_{14+} - 1) + 0.3 * \texttt{HM}_{13-}, \text{ with}$$

$\texttt{HM}_{14+}$ the number of household members aged 14 and over (at the end of the income reference period),
$\texttt{HM}_{13-}$ the number of household members aged 13 or less (at the end of the income reference period).

The **within-household non-response inflation factor** (HX025) is used to correct for partial unit or individual non-response. However, this applies on average only to 5 countries per year, namely Bulgaria, Germany, Greece, Portugal and Romania, with average non-response of around 1.28% within the EU-SILC 2007 – 2011 surveys. For all other countries and individuals, HX025 = 1.

In Table 5 on the page 20, we provide descriptive statistics for one of the used EU-SILC data sets, namely "EUSILC UDB 2011 version 2 of August 2013". The descriptive statistics include sample and population size, and summary statistics for the income converted to purchasing power parities (ppps). The the average sample size is 7,836, the average mean income is 15,886 ppps, the smallest income is −318,771 ppps for Luxembourg and the largest is 1,535,588 ppps for Finland. Note that the mean incomes are slightly different than the ones given in Table 7 since here the negative incomes are included. The population size of a country is computed as the sum of the product of the household size (HX040) and the household weight (DB090).

Table 5: Descriptive statistics for 2011
("EUSILC UDB 2011 version 2 of August 2013")

	Sample size	Population size	Min income	1st income quartile	Median income	Mean income	3rd income quartile	Max income
AT	6 187	8 315 881	0	14 987	20 250	22 458	26 693	278 109
BE	5 910	10 826 442	-25 929	12 783	17 992	19 452	23 858	1 514 598
BG	6 554	7 518 649	0	3 616	5 700	6 725	8 283	234 696
CH	7 502	7 619 680	-37 754	16 522	23 069	26 541	31 750	523 184
CY	3 917	839 751	0	13 849	19 238	22 378	26 698	857 039
CZ	8 866	10 434 558	-356	7 761	9 858	11 167	12 982	136 139
DE	13 512	80 845 125	-270 224	13 108	18 241	20 642	25 150	563 242
DK	5 331	5 512 919	-119 447	13 841	18 680	20 228	24 393	195 271
EE	4 993	1 328 259	-3 878	5 036	7 334	8 612	10 765	65 872
EL	6 029	10 991 212	-1 672	7 500	11 480	13 197	16 520	189 878
ES	13 109	45 900 276	-25 357	8 360	12 906	14 698	19 108	121 282
FI	9 351	5 294 659	-567	12 993	17 742	19 633	23 554	1 535 588
FR	11 360	61 359 753	-10 115	13 290	18 053	21 568	24 672	833 237
HR	6 403	4 225 193	-2 507	4 862	7 304	8 122	10 221	57 693
HU	11 685	9 850 181	-2 609	5 162	7 017	7 903	9 493	57 133
IS	3 018	300 766	-18 558	13 464	17 135	18 703	21 846	256 820
IT	19 399	60 683 909	-19 427	10 464	15 513	17 538	21 581	1 060 375
LT	5 201	3 234 482	-1 783	4 080	6 165	7 096	8 916	61 404
LU	5 464	497 640	-318 771	19 229	26 667	30 048	37 153	420 018
LV	6 599	2 049 851	-6 080	3 856	5 666	6 953	8 775	46 466
MT	4 076	412 580	-11 391	9 996	14 033	15 683	19 300	80 568
NL	10 492	16 526 278	-96 850	14 278	18 748	20 825	24 912	497 711
NO	4 628	4 961 793	-29 401	19 177	24 196	25 939	30 601	386 971
PL	12 871	37 473 013	-3 192	5 684	8 207	9 493	11 504	218 700
PT	5 740	10 636 979	290	6 651	9 583	11 860	14 114	145 834
RO	7 675	21 501 653	-324	2 286	3 554	4 056	5 196	70 562
SE	6 717	9 531 043	-88 299	13 703	18 474	19 592	23 720	569 650
SI	9 247	2 003 382	-8 230	10 461	13 797	14 814	17 923	98 549
SK	5 200	5 392 446	136	6 806	8 855	9 802	11 820	472 196
UK	8 058	61 770 154	-87 420	12 137	17 190	20 856	25 089	665 157

C. Data sets and tables

The exact names of the data sets that we use in this work are

"EUSILC UDB 2007 version 6 of August 2011",
"EUSILC UDB 2008 version 5 of March 2012",
"EUSILC UDB 2009 version 4 of August 2012",
"EUSILC UDB 2010 version 4 of August 2013",
"EUSILC UDB 2011 version 2 of August 2013",

as obtained from the EU-SILC User Database (UDB).

In terms of variables, we use the equivalised disposable household income converted in purchasing power parities (for more details see Appendix B). For computational reasons, we set all negative income values to zero. In fact, there are very few zero and negative incomes in the EU-SILC 2007 – 2011 surveys (the average is 0.32%) and they do not affect substantially the total income distribution.

In this appendix, we also provide tables with the estimated parameters $\hat{a}$, $\hat{b}$ and $\hat{p}$ for the Dagum distribution for the observed European countries and years (see Table 6) and the empirical and parametric Gini coefficients, means and medians (see Table 7).

Table 6 lists the Dagum estimates for the a, b and p parameters for all the observed countries from 2007 to 2011 and their respective standard errors. Table 7 shows the empirical estimates for the Gini coefficient, the mean and the median and their parametric representations, estimated using the suggested parametric model along with standard errors. The empirical estimates given in the tables are computed in `R` with the EU-SILC microdata and the functions `gini` (`R` package `reldist` (Handcock (2015)), `weighted.mean` (package `stats`) and `wtd.quantile` (type `"i/n"`, package `Hmisc` (Harrell Jr et al. (2015)), respectively. Note that the mean and the median are given in purchasing power parities (ppp) (explained in Appendix A).

The standard errors of the parametric estimates were computed with a parametric bootstrap as explained in section 3.4.

For Eurostat's official estimates of the Gini coefficients see Eurostat (2013).

Table 6: Estimated distribution parameters (2007 – 2011)

	$\hat{a}$	SE($\hat{a}$)	$\hat{b}$	SE($\hat{b}$)	$\hat{p}$	SE($\hat{p}$)
2007						
AT	4.1376	(0.084)	19450.56	(336.87)	0.7904	(0.036)
BE	4.2481	(0.095)	18322.31	(313.30)	0.7074	(0.032)
BG	3.8027	(0.110)	4818.99	(95.75)	0.4166	(0.019)
CY	3.3789	(0.083)	17239.85	(489.76)	1.1180	(0.070)
CZ	3.9684	(0.060)	8720.24	(131.76)	1.0729	(0.041)
DE	3.7768	(0.049)	19570.74	(221.79)	0.7432	(0.020)
DK	4.9917	(0.111)	19087.24	(267.22)	0.6652	(0.029)
EE	3.2437	(0.074)	7284.70	(172.31)	0.7794	(0.038)
EL	3.1212	(0.065)	12863.59	(291.76)	0.7786	(0.034)
ES	3.6947	(0.059)	16355.22	(207.82)	0.5981	(0.017)
FI	3.9862	(0.063)	15377.67	(216.27)	0.9489	(0.034)

	$\hat{a}$	SE($\hat{a}$)	$\hat{b}$	SE($\hat{b}$)	$\hat{p}$	SE($\hat{p}$)
FR	3.8277	(0.055)	15317.79	(212.10)	0.9647	(0.033)
HU	4.1839	(0.070)	6937.75	(98.15)	0.8263	(0.030)
IT	3.5292	(0.041)	17255.24	(180.03)	0.6583	(0.015)
LT	3.1623	(0.074)	6687.41	(162.42)	0.7362	(0.035)
LU	3.5495	(0.088)	26226.17	(730.92)	1.0793	(0.068)
LV	2.9245	(0.073)	6329.09	(178.71)	0.7765	(0.040)
NL	3.8529	(0.057)	17307.33	(253.13)	1.0571	(0.038)
PL	3.2601	(0.044)	6152.88	(86.39)	0.8241	(0.023)
PT	2.5078	(0.057)	8003.65	(307.90)	1.2815	(0.081)
RO	2.9747	(0.058)	3615.72	(73.51)	0.6131	(0.022)
SE	5.2231	(0.103)	18835.17	(213.52)	0.5731	(0.020)
SI	4.7012	(0.084)	14391.72	(178.82)	0.7255	(0.027)
SK	4.4924	(0.101)	6135.78	(102.27)	0.7729	(0.036)
UK	3.2715	(0.054)	20528.32	(351.72)	0.8025	(0.028)
2008						
AT	3.9057	(0.080)	18943.87	(363.24)	0.9478	(0.045)
BE	4.0898	(0.077)	18401.14	(281.21)	0.7615	(0.029)
BG	2.9651	(0.073)	5510.52	(148.84)	0.7498	(0.038)
CY	3.5892	(0.091)	18612.47	(508.89)	1.0328	(0.064)
CZ	4.1616	(0.057)	9780.06	(123.81)	1.0013	(0.034)
DE	3.6960	(0.057)	20022.28	(281.31)	0.7762	(0.025)
DK	4.9455	(0.102)	19939.14	(265.26)	0.6537	(0.026)
EE	3.4370	(0.081)	8614.37	(190.24)	0.7327	(0.035)
EL	3.3019	(0.070)	13830.47	(298.93)	0.7556	(0.033)
ES	3.8250	(0.057)	17791.22	(204.67)	0.5670	(0.015)
FI	3.9590	(0.060)	16942.70	(235.17)	0.9158	(0.032)
FR	3.3732	(0.049)	16027.11	(288.00)	1.2719	(0.050)
HU	4.1306	(0.069)	6768.50	(97.82)	0.9043	(0.034)
IT	3.7362	(0.043)	18476.74	(182.07)	0.6294	(0.014)
LT	3.1620	(0.073)	7789.24	(192.88)	0.7792	(0.038)
LU	3.5398	(0.085)	25783.55	(699.88)	1.1279	(0.070)
LV	2.7223	(0.059)	8125.85	(223.47)	0.7927	(0.037)
NL	3.8604	(0.057)	19129.82	(283.62)	1.0260	(0.037)
PL	3.2459	(0.043)	7170.10	(105.08)	0.8803	(0.026)
PT	2.7003	(0.062)	9041.75	(298.67)	1.1156	(0.065)
RO	3.2052	(0.063)	3986.50	(73.27)	0.5783	(0.021)
SE	5.1931	(0.104)	20964.53	(242.96)	0.5740	(0.021)
SI	4.7998	(0.084)	15572.23	(179.98)	0.6830	(0.023)
SK	4.8399	(0.105)	7690.53	(112.46)	0.6655	(0.028)
UK	3.1794	(0.053)	20053.18	(378.36)	0.8447	(0.031)
2009						
AT	4.1800	(0.085)	20666.36	(343.79)	0.7854	(0.034)
BE	4.2319	(0.084)	19176.23	(303.38)	0.7560	(0.031)
BG	3.2929	(0.071)	6831.65	(142.40)	0.6659	(0.028)
CY	3.2433	(0.086)	16994.09	(609.72)	1.2894	(0.100)
CZ	4.1460	(0.064)	9388.07	(130.90)	1.0446	(0.039)
DE	3.7771	(0.053)	20098.35	(253.91)	0.7565	(0.022)
DK	5.3999	(0.120)	21384.05	(258.61)	0.5452	(0.022)
EE	3.2366	(0.077)	8712.63	(214.65)	0.8465	(0.043)

	$\hat{a}$	SE($\hat{a}$)	$\hat{b}$	SE($\hat{b}$)	$\hat{p}$	SE($\hat{p}$)
EL	3.3262	(0.069)	14107.05	(291.89)	0.7769	(0.033)
ES	4.0121	(0.059)	19257.04	(201.43)	0.4799	(0.012)
FI	4.0916	(0.063)	18042.75	(243.28)	0.8712	(0.030)
FR	3.3356	(0.048)	16322.51	(294.64)	1.2255	(0.048)
HU	4.1012	(0.060)	6884.16	(93.57)	0.9582	(0.034)
IT	3.6733	(0.042)	18717.21	(181.47)	0.6238	(0.014)
LT	3.0780	(0.074)	8538.97	(217.99)	0.7374	(0.036)
LU	3.3954	(0.077)	25861.48	(688.11)	1.0930	(0.064)
LV	2.9410	(0.065)	8882.64	(210.07)	0.6701	(0.029)
NL	4.0081	(0.062)	20381.42	(277.31)	0.8840	(0.031)
PL	3.2815	(0.043)	7696.39	(110.16)	0.9008	(0.027)
PT	2.8232	(0.061)	9329.67	(267.09)	1.0363	(0.054)
RO	3.4099	(0.070)	4512.56	(73.69)	0.5451	(0.019)
SE	5.1928	(0.103)	22825.90	(247.95)	0.5271	(0.018)
SI	4.8829	(0.082)	15948.49	(180.62)	0.7107	(0.025)
SK	4.4231	(0.096)	8823.57	(140.19)	0.7282	(0.032)
UK	3.2441	(0.053)	18295.71	(325.64)	0.8516	(0.031)
2010						
AT	3.8682	(0.075)	19295.13	(362.13)	0.9785	(0.046)
BE	4.2305	(0.095)	19592.69	(343.75)	0.7023	(0.033)
BG	3.4006	(0.073)	7115.44	(140.02)	0.6461	(0.027)
CY	3.2462	(0.078)	17047.74	(511.93)	1.1979	(0.077)
CZ	4.1544	(0.065)	9782.29	(144.46)	1.0023	(0.039)
DE	3.6051	(0.050)	18408.35	(247.21)	0.8913	(0.027)
DK	5.3760	(0.125)	22411.00	(267.99)	0.4759	(0.019)
EE	3.3177	(0.080)	8437.33	(198.93)	0.7881	(0.039)
EL	3.2704	(0.063)	13934.90	(281.49)	0.8003	(0.033)
ES	3.8570	(0.060)	18681.71	(212.89)	0.4718	(0.013)
FI	4.1262	(0.061)	17761.85	(230.00)	0.8970	(0.030)
FR	3.4446	(0.048)	17745.89	(279.65)	1.0296	(0.036)
HU	4.2323	(0.066)	6908.70	(92.36)	0.9135	(0.033)
IT	3.8523	(0.049)	19226.48	(187.57)	0.5732	(0.013)
LT	3.0160	(0.066)	7628.10	(174.71)	0.6544	(0.028)
LU	3.5952	(0.079)	26756.06	(606.86)	0.9773	(0.051)
LV	3.1122	(0.067)	7729.01	(164.04)	0.6122	(0.025)
NL	4.1557	(0.063)	19937.42	(253.30)	0.8806	(0.029)
PL	3.3588	(0.049)	8242.92	(118.33)	0.8225	(0.025)
PT	2.9055	(0.064)	9638.01	(269.49)	1.0219	(0.054)
RO	3.4451	(0.067)	4541.37	(77.55)	0.5883	(0.021)
SE	5.2869	(0.108)	22201.91	(249.83)	0.5252	(0.019)
SI	4.6152	(0.080)	14843.25	(179.48)	0.7206	(0.025)
SK	4.5374	(0.106)	9917.55	(151.74)	0.6275	(0.028)
UK	3.1212	(0.052)	17612.79	(350.80)	0.9403	(0.037)
2011						
AT	4.2863	(0.097)	23106.61	(391.81)	0.6851	(0.032)
BE	4.3430	(0.102)	20413.01	(335.27)	0.6712	(0.030)
BG	3.2583	(0.072)	7094.97	(142.62)	0.6165	(0.025)
CY	3.3681	(0.081)	18468.58	(516.42)	1.1077	(0.067)
CZ	4.0603	(0.064)	10033.52	(149.34)	0.9878	(0.038)

	$\hat{a}$	SE($\hat{a}$)	$\hat{b}$	SE($\hat{b}$)	$\hat{p}$	SE($\hat{p}$)
DE	3.8206	(0.051)	20394.01	(244.54)	0.7560	(0.021)
DK	4.7406	(0.112)	22619.84	(323.91)	0.5635	(0.024)
EE	3.4249	(0.080)	8923.23	(198.05)	0.6697	(0.031)
EL	3.4499	(0.076)	13977.85	(283.40)	0.6342	(0.027)
ES	3.7775	(0.059)	18207.91	(209.31)	0.4732	(0.012)
FI	4.0336	(0.066)	18331.54	(265.45)	0.8975	(0.033)
FR	3.3272	(0.048)	17390.27	(290.64)	1.1053	(0.040)
HU	3.6470	(0.053)	6934.27	(104.35)	1.0294	(0.036)
IT	3.9594	(0.049)	20412.89	(186.23)	0.5083	(0.011)
LT	3.5089	(0.081)	7845.62	(156.42)	0.5870	(0.025)
LU	3.6785	(0.075)	27220.59	(553.13)	0.9582	(0.046)
LV	3.1157	(0.065)	7173.01	(146.06)	0.6526	(0.026)
NL	4.0893	(0.060)	19274.93	(250.39)	0.9489	(0.032)
PL	3.4433	(0.049)	9073.83	(124.79)	0.7843	(0.024)
PT	2.8431	(0.057)	9302.14	(254.51)	1.0790	(0.054)
RO	3.7352	(0.075)	4903.64	(74.97)	0.4816	(0.017)
SE	5.1024	(0.113)	22149.00	(276.91)	0.5485	(0.021)
SI	4.7511	(0.081)	15652.29	(178.73)	0.6713	(0.022)
SK	4.6752	(0.111)	10723.36	(158.87)	0.5866	(0.025)
UK	3.1609	(0.053)	18077.48	(355.47)	0.9304	(0.036)

Table 7: Gini coefficients, mean and median (2007 – 2011)

	Gini		SE(Gini	Mean		SE(Mean	Median		SE(Median
	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)
2007									
AT	0.2619	0.2579	(0.003)	19955.03	19748.77	(122.49)	17808.03	17920.23	(101.92)
BE	0.2623	0.2603	(0.003)	17781.85	17808.71	(115.45)	16311.07	16252.42	(97.66)
BG	0.3529	0.3488	(0.004)	3835.86	3748.78	(40.75)	3298.93	3288.03	(33.35)
CY	0.2978	0.2886	(0.005)	21158.30	20906.49	(205.30)	18244.05	18033.35	(153.31)
CZ	0.2527	0.2477	(0.002)	10023.32	9943.47	(48.73)	8840.71	8934.98	(40.25)
DE	0.2989	0.2871	(0.002)	19836.96	19655.23	(97.27)	17324.67	17452.31	(82.75)
DK	0.2451	0.2277	(0.002)	18255.46	17990.66	(101.82)	16865.51	16901.41	(87.78)
EE	0.3341	0.3280	(0.004)	7741.81	7689.45	(73.16)	6490.87	6519.01	(55.99)
EL	0.3427	0.3406	(0.004)	13628.90	13708.96	(132.80)	11436.55	11456.10	(91.48)
ES	0.3126	0.3140	(0.003)	14884.04	15037.44	(83.78)	13117.82	13234.11	(71.27)
FI	0.2616	0.2543	(0.002)	16940.01	16778.86	(82.62)	15240.21	15097.27	(68.31)
FR	0.2656	0.2636	(0.002)	16949.41	16959.25	(86.48)	15148.29	15118.76	(68.56)
HU	0.2555	0.2518	(0.002)	7195.66	7147.28	(38.04)	6490.14	6499.80	(32.64)
IT	0.3222	0.3178	(0.002)	16552.40	16631.92	(72.01)	14404.92	14459.45	(61.23)
LT	0.3382	0.3414	(0.005)	6869.35	6922.04	(71.97)	5713.35	5805.62	(50.84)
LU	0.2736	0.2768	(0.004)	30737.93	30882.05	(288.22)	26839.20	27010.84	(216.14)
LV	0.3536	0.3629	(0.005)	6727.86	6868.52	(77.36)	5515.25	5585.13	(55.73)
NL	0.2725	0.2561	(0.002)	20052.17	19774.57	(103.44)	17537.36	17653.52	(79.61)
PL	0.3218	0.3216	(0.002)	6645.75	6648.13	(37.39)	5608.55	5651.94	(26.93)
PT	0.3691	0.3814	(0.006)	11734.87	11956.58	(161.61)	8950.76	9136.22	(88.12)
RO	0.3783	0.3808	(0.004)	3447.55	3473.98	(31.15)	2876.40	2818.82	(23.36)
SE	0.2339	0.2306	(0.002)	17035.04	16883.52	(83.11)	15907.47	15990.61	(79.35)
SI	0.2330	0.2341	(0.002)	13998.20	14004.74	(69.32)	12917.11	13022.78	(58.92)
SK	0.2447	0.2397	(0.003)	6182.34	6123.64	(41.16)	5607.93	5647.24	(33.27)
UK	0.3276	0.3228	(0.003)	21969.53	21905.19	(154.97)	18662.18	18637.11	(113.02)

	Gini		SE(Gini	Mean		SE(Mean	Median		SE(Median
	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)
2008									
AT	0.2619	0.2595	(0.003)	20850.51	20748.18	(139.39)	18537.41	18583.87	(112.31)
BE	0.2731	0.2638	(0.003)	18638.45	18455.54	(119.35)	16742.81	16705.47	(101.03)
BG	0.3593	0.3613	(0.005)	5842.11	5854.62	(69.07)	4762.96	4784.30	(48.20)
CY	0.2795	0.2765	(0.004)	21554.68	21483.50	(208.05)	19079.34	18844.94	(159.81)
CZ	0.2475	0.2402	(0.002)	10914.45	10779.42	(48.07)	9724.99	9784.30	(39.80)
DE	0.3001	0.2894	(0.002)	20774.41	20534.31	(103.47)	18006.40	18133.17	(86.59)
DK	0.2485	0.2311	(0.003)	18996.58	18689.58	(108.08)	17600.61	17536.03	(97.82)
EE	0.3092	0.3156	(0.004)	8635.08	8738.55	(79.88)	7561.65	7547.42	(63.89)
EL	0.3315	0.3252	(0.004)	14254.78	14339.31	(120.86)	12029.31	12225.90	(90.72)
ES	0.3083	0.3096	(0.002)	15761.32	15942.17	(83.60)	13948.62	14158.07	(73.25)
FI	0.2632	0.2584	(0.002)	18407.67	18277.31	(96.08)	16554.57	16421.84	(74.19)
FR	0.2895	0.2816	(0.003)	20676.97	20443.46	(126.61)	17566.06	17633.52	(85.61)
HU	0.2519	0.2486	(0.002)	7237.80	7213.09	(37.26)	6596.56	6540.32	(31.72)
IT	0.3098	0.3055	(0.002)	17315.90	17347.88	(72.95)	15262.33	15331.12	(58.14)
LT	0.3398	0.3362	(0.004)	8241.32	8275.14	(85.82)	6946.49	6949.91	(59.94)
LU	0.2765	0.2748	(0.004)	30905.79	30896.30	(292.17)	26942.93	27005.71	(209.78)
LV	0.3773	0.3869	(0.005)	8925.64	9142.16	(111.86)	7254.53	7185.94	(73.08)
NL	0.2728	0.2574	(0.002)	21929.36	21615.38	(112.76)	19141.46	19306.45	(89.02)
PL	0.3201	0.3176	(0.003)	8004.69	7981.99	(45.84)	6731.61	6782.51	(33.93)
PT	0.3578	0.3624	(0.005)	12007.61	12073.74	(158.41)	9502.25	9555.44	(89.81)
RO	0.3597	0.3619	(0.004)	3645.18	3668.98	(31.15)	3064.51	3067.93	(23.39)
SE	0.2370	0.2317	(0.002)	18916.07	18800.68	(89.78)	17799.25	17791.27	(88.41)
SI	0.2343	0.2342	(0.002)	14847.51	14829.97	(67.85)	13792.14	13843.84	(61.92)
SK	0.2363	0.2345	(0.003)	7311.52	7257.03	(42.70)	6761.53	6785.02	(40.67)
UK	0.3390	0.3275	(0.003)	22357.21	22056.34	(162.18)	18542.83	18592.48	(117.45)
2009									
AT	0.2566	0.2559	(0.003)	21029.55	20908.17	(137.86)	18915.55	19013.27	(118.88)

	Gini		SE(Gini	Mean		SE(Mean	Median		SE(Median
	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)
BE	0.2603	0.2558	(0.003)	19086.87	19105.65	(123.35)	17502.11	17420.06	(103.06)
BG	0.3336	0.3381	(0.004)	6638.28	6693.26	(59.93)	5725.48	5684.43	(47.78)
CY	0.2915	0.2924	(0.005)	22090.55	22141.36	(259.00)	19136.84	18871.89	(169.13)
CZ	0.2507	0.2386	(0.002)	10695.53	10503.76	(48.82)	9442.89	9525.03	(40.73)
DE	0.2911	0.2855	(0.002)	20503.78	20329.31	(105.97)	17949.25	18053.32	(81.13)
DK	0.2433	0.2280	(0.002)	18921.53	18864.99	(101.78)	17917.79	17959.91	(98.28)
EE	0.3141	0.3217	(0.004)	9402.50	9543.38	(91.47)	8100.27	8096.44	(68.42)
EL	0.3282	0.3204	(0.004)	14757.02	14781.26	(115.76)	12532.78	12641.05	(93.18)
ES	0.3173	0.3150	(0.002)	15787.03	16022.03	(84.24)	13989.64	14366.90	(73.99)
FI	0.2593	0.2535	(0.002)	19155.63	19006.03	(93.72)	17367.45	17201.38	(75.39)
FR	0.2987	0.2869	(0.003)	20953.19	20613.22	(122.44)	17735.51	17718.64	(85.88)
HU	0.2468	0.2465	(0.002)	7494.04	7495.56	(35.92)	6828.52	6784.94	(30.44)
IT	0.3143	0.3113	(0.002)	17537.12	17536.80	(76.34)	15262.45	15419.21	(64.32)
LT	0.3551	0.3502	(0.005)	8933.93	8906.36	(91.64)	7299.63	7390.57	(67.89)
LU	0.2913	0.2886	(0.004)	31133.56	31033.76	(295.18)	27106.30	26804.79	(204.19)
LV	0.3735	0.3753	(0.004)	8833.42	8950.96	(95.82)	7296.22	7255.45	(69.32)
NL	0.2683	0.2577	(0.002)	21953.58	21658.04	(114.37)	19364.08	19513.93	(90.06)
PL	0.3141	0.3124	(0.003)	8641.87	8625.20	(51.18)	7360.95	7358.58	(36.74)
PT	0.3538	0.3516	(0.005)	11828.69	11768.91	(131.45)	9424.70	9493.61	(85.48)
RO	0.3486	0.3486	(0.004)	3989.42	4005.67	(31.34)	3426.73	3422.85	(26.35)
SE	0.2464	0.2397	(0.002)	20067.66	19872.66	(104.99)	18823.02	18818.86	(94.96)
SI	0.2274	0.2272	(0.002)	15378.22	15379.35	(68.52)	14329.25	14390.62	(61.77)
SK	0.2483	0.2480	(0.003)	8679.06	8636.86	(58.81)	7823.80	7944.77	(50.43)
UK	0.3234	0.3205	(0.003)	20074.67	20080.47	(147.34)	16831.51	17051.33	(107.12)
2010									
AT	0.2611	0.2599	(0.003)	21490.55	21422.63	(143.62)	19131.60	19144.67	(109.74)
BE	0.2653	0.2619	(0.003)	19045.89	18999.47	(125.23)	17348.81	17324.22	(107.78)
BG	0.3318	0.3310	(0.004)	6832.00	6838.53	(60.70)	5892.06	5870.07	(46.84)
CY	0.2980	0.2964	(0.005)	21584.03	21563.74	(221.35)	18349.81	18377.67	(152.21)

	Gini		SE(Gini	Mean		SE(Mean	Median		SE(Median
	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)
CZ	0.2494	0.2406	(0.002)	10936.59	10789.13	(54.38)	9671.24	9789.71	(43.90)
DE	0.2904	0.2855	(0.002)	20131.43	20046.71	(104.46)	17594.19	17596.83	(76.44)
DK	0.2524	0.2424	(0.003)	19094.48	18851.84	(114.17)	17968.99	17956.70	(104.27)
EE	0.3123	0.3200	(0.004)	8791.46	8901.52	(83.92)	7420.38	7607.84	(62.93)
EL	0.3284	0.3231	(0.004)	14738.57	14852.28	(121.33)	12613.65	12634.45	(89.76)
ES	0.3330	0.3285	(0.002)	15180.85	15417.92	(86.77)	13353.79	13659.48	(73.34)
FI	0.2542	0.2494	(0.002)	18991.29	18878.10	(89.46)	17232.06	17114.07	(71.31)
FR	0.2978	0.2883	(0.003)	21001.48	20704.93	(116.35)	17890.99	17954.21	(88.82)
HU	0.2406	0.2420	(0.002)	7333.18	7358.19	(36.26)	6715.73	6704.12	(28.15)
IT	0.3114	0.3064	(0.002)	17331.40	17302.48	(74.95)	15224.48	15399.98	(64.46)
LT	0.3689	0.3690	(0.005)	7504.53	7548.81	(82.77)	6069.29	6183.13	(59.20)
LU	0.2775	0.2797	(0.004)	30031.86	30222.77	(261.42)	26634.14	26518.90	(187.41)
LV	0.3605	0.3654	(0.004)	7266.96	7351.72	(73.66)	5974.10	6087.21	(54.65)
NL	0.2538	0.2489	(0.002)	21091.32	21028.45	(102.03)	18836.06	19092.73	(81.25)
PL	0.3110	0.3126	(0.003)	8811.79	8831.92	(49.40)	7587.10	7584.31	(38.03)
PT	0.3366	0.3426	(0.005)	11829.43	11925.23	(129.06)	9738.50	9737.83	(82.21)
RO	0.3328	0.3368	(0.003)	4132.12	4173.98	(31.51)	3543.97	3589.61	(25.28)
SE	0.2399	0.2361	(0.002)	19474.18	19319.95	(102.90)	18341.44	18344.72	(95.75)
SI	0.2380	0.2388	(0.002)	14400.54	14429.13	(66.63)	13353.65	13376.14	(62.00)
SK	0.2588	0.2546	(0.003)	9285.11	9186.54	(58.84)	8370.22	8495.83	(54.22)
UK	0.3278	0.3249	(0.004)	20361.32	20426.45	(155.33)	16959.03	17132.89	(109.86)
2011									
AT	0.2631	0.2608	(0.003)	22457.57	22177.20	(146.51)	20249.83	20277.48	(124.67)
BE	0.2620	0.2593	(0.003)	19461.71	19425.70	(126.50)	17992.35	17809.84	(110.18)
BG	0.3509	0.3495	(0.004)	6724.72	6717.42	(59.60)	5699.85	5668.53	(46.35)
CY	0.2914	0.2902	(0.004)	22377.59	22339.71	(217.87)	19238.34	19250.17	(160.83)
CZ	0.2524	0.2471	(0.002)	11167.05	11062.35	(57.42)	9858.34	9991.60	(47.82)
DE	0.2877	0.2824	(0.002)	20672.47	20586.45	(97.06)	18240.69	18335.67	(82.29)
DK	0.2666	0.2542	(0.003)	20417.37	20127.35	(130.46)	18680.15	18769.92	(121.48)

	Gini		SE(Gini	Mean		SE(Mean	Median		SE(Median
	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)	Empirical	Parametric	Parametric)
EE	0.3189	0.3252	(0.004)	8614.10	8706.10	(80.15)	7333.56	7497.71	(66.16)
EL	0.3348	0.3285	(0.004)	13200.96	13293.08	(114.20)	11479.69	11461.45	(94.19)
ES	0.3365	0.3342	(0.002)	14735.77	15046.75	(85.81)	12905.98	13245.41	(73.61)
FI	0.2581	0.2550	(0.002)	19632.87	19564.23	(102.66)	17742.45	17651.26	(83.69)
FR	0.3082	0.2939	(0.003)	21569.64	21107.10	(119.75)	18053.47	18120.09	(86.51)
HU	0.2681	0.2723	(0.002)	7903.37	7958.88	(40.49)	7016.77	7010.78	(31.07)
IT	0.3189	0.3120	(0.002)	17541.32	17420.44	(74.42)	15513.43	15585.70	(66.97)
LT	0.3284	0.3314	(0.004)	7096.71	7188.81	(66.09)	6164.57	6221.04	(55.27)
LU	0.2707	0.2747	(0.003)	30090.98	30341.79	(239.73)	26666.64	26783.74	(178.39)
LV	0.3534	0.3582	(0.004)	6955.01	7037.50	(65.51)	5665.68	5845.11	(50.30)
NL	0.2526	0.2479	(0.002)	20922.34	20926.73	(101.37)	18748.29	18932.11	(81.74)
PL	0.3105	0.3091	(0.002)	9493.80	9473.54	(53.52)	8206.76	8195.16	(43.37)
PT	0.3424	0.3462	(0.005)	11859.76	11914.78	(120.88)	9583.17	9649.25	(76.63)
RO	0.3328	0.3354	(0.003)	4056.21	4085.97	(31.61)	3553.66	3586.19	(27.66)
SE	0.2430	0.2398	(0.002)	19608.12	19544.00	(109.09)	18473.53	18452.82	(100.75)
SI	0.2383	0.2379	(0.002)	14814.77	14825.06	(70.30)	13796.71	13817.96	(61.81)
SK	0.2567	0.2536	(0.003)	9801.53	9684.39	(64.03)	8855.06	9007.66	(59.18)
UK	0.3297	0.3217	(0.003)	20867.25	20781.65	(161.56)	17190.29	17508.41	(113.50)